COMBINING TIME FREQUENCY REPRESENTATION AND PARAMETRIC ANALYSIS FOR THE ENHANCEMENT OF TRANSIENTS IN SLEEP EEG SIGNAL

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Abstract - **The study of the electroencephalographic (EEG) signal contributes to sleep analysis. In the microstructure of the sleep EEG signal, transient patterns are characterized by their frequency content and their time duration. The Time–Frequency Representations (TFR) take into account these time – frequency characteristics but the lower energy transient signals are masked by higher energy ones. In order to overcome this problem, we introduced a method to decompose signals into a summation of oscillatory components with time varying frequency, amplitude and phase characteristics, based on the Tufts-Kumaresan algorithm. The resulting parameters, i.e. amplitude and frequency, are then used to train joint linear filtering operations of the TFR in the time - frequency domain. The aim of this work is to improve the classical TFR analysis for detecting frequency transients over short time duration, to reduce the amount of useful information to few parameters that help medical doctors to analyze the microstructure of sleep by correlating information estimated from different signals.**

Keywords - **Electroencephalogram, parametric analysis, time frequency representation, transient detection.**

I. INTRODUCTION

The physiological investigation of sleep implies the acquisition and the study of several types of signals. The polysomnographic recordings allow to analyze at the same time the organization of sleep in stages and cycles and, in a finer way, the microstructure of the registered signals. The brain activities are characterized by their frequency, their amplitude, their morphology, their stability, their topography and their ability to react. They are classified according to their wave band. These constituents constitute the microstructure of the sleep and the stage of sleep is largely identified from the microstructure.

Within the framework of the electroencephalographic (EEG) signal in particular, it turns out indispensable to make the recognition of the transient phenomena (points vertexes, spindles, K complexes, micro-arousal reactions). Indeed, the presence of specific waves such as spindles allows to distinguish the various stages of the sleep and, so, to draw a global representation of a night of sleep and to estimate its general organization (hypnogram).

Furthermore, the spindles, the K complexes and especially the micro-arousals also allow to characterize the micro-structure of the electric activity of the brain and the correlation of these phenomena with non EEG signals (for example the respiratory flux) allows us to deepen the knowledge on the brain mechanisms connected to the sleep disorders (e.g. obstructive sleep apneas, central sleep apneas, periodic limb movement disorders).

The visual inspection of temporal recordings by the specialist leads to the estimation of the frequency contents (the rhythms) and their locations in time. The Time - Frequency Representations (TFR) constitute a privileged tool for diagnosis assistance [1] as far as the various spectral constituents are separately shown with their temporal evolutions.

The major drawback of these techniques is connected to the masking of the constituents with weak energy by those with high energy. Indeed, the transient phenomena often appear in the sleep EEG as components with high frequency and weak energy. They are, in addition, embedded in a characteristic component of the stage which is generally of low frequency and high energy [2], [3], as shown in Fig. 1.

In a general way, a tool of data processing stemming from biomedical signals such as the EEGs, should allow at the same moment to extract relevant information and to propose an easily interpretable display by the physician. Furthermore the results from EEG signal analysis have to be validated and completed by combining other information resulting from the other types of signals (electrocardiogram, electromyogram, respiratory flux, etc.).

The aim of the present work is to bring a complement to the TFR by the modal analysis, a parametric approach, using the principle of the singular value decomposition. This treatment allows to appreciate the meaning of a frequency estimated on a brief interval. For example, in Fig. 1, a spindle is superimposed to the delta rhythm. In this example, the spindle is clearly detected by visual inspection. In other cases, it may be difficult to distinguish high frequencies due to noise from high frequency signals.
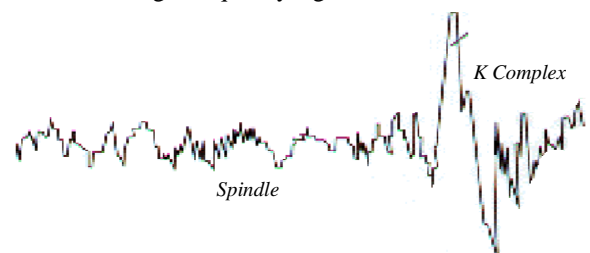

Fig. 1. Example of transients in sleep EEG signal.

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Abstract

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To fall in with the requirements of the application in real situation, we first realized an interface allowing to quickly investigate the various recording channels and to ask, in an interactive way, for one of the Time – Frequency or parametric proposed analysis.

II. METHODOLOGY

The modal analysis leans on the modeling of the EEG signal as the combination of sinusoidal components each with its frequency, its phase and its amplitude, which evolve during time according to the brain activity during sleep.

A useful way of description of such time-series is to predict them and therefore construct a model of their dynamics. Typically, biomedical data like EEG signal has strong non-stationarities. In such cases, it is very helpful to first resolve the non-stationarities by a segmentation into stationarity parts and then to identify the deterministic components inherent to the data.

The method, based on the algorithms of Prony and Tufts-Kumaresan [4, 5], segments the signal in successive phases of constant duration (for example 1 second each) and, estimates, in every step, the parameters (frequency, phase and amplitude) of the most stable sinusoidal constituents (dominants), constituting the EEG signal in the window of current analysis, as shown in (1) and illustrated in Fig. 2. The data segmentation here applied takes into account the EEG sleep transient characteristics: a spindle or a micro-arousal reaction has a duration of 0.5 – 1 second about. Hence, the signal is decomposed over segments of one-second length and the overlapping between successive segments allows to reduce boundary effects.

By this method, N points over one second of EEG data can be written as:

$$x(n) = \sum_{m=1}^{P} A_m \cdot \cos(2 \cdot \pi \cdot F_m \cdot n - \Phi_m) + v(n), \qquad 1 \leq n \leq N \qquad (1)$$

where P is the number of sinusoidal components, A_m, F_m and Φ_m are respectively the amplitude, frequency and phase of the mth component and $v(n)$ is the additive noise.

The method of Prony allows to define the polynomial $c(z)$ by:

$$c(z) = \prod_{m=1}^{P}(1 - 2 \cdot \cos(2 \cdot \pi \cdot F_m) \cdot z^{-1} + z^{-2}) = \sum_{k=0}^{2 \cdot P} c_k \cdot z^{-k}, \qquad c_0 = 1 \qquad (2)$$

and to write (1) as:

$$x(n) = -\sum_{k=1}^{2 \cdot P} c_k \cdot x(n-k), \qquad \forall n \qquad (3)$$

Prony's method uses (3) by estimating $c(z)$ as the solution of the set of equations

$$\begin{bmatrix} x(2P) \\ x(2P+1) \\ \vdots \\ x(L-1) \end{bmatrix} + \begin{bmatrix} x(2P-1) & x(2P-2) & \cdots & x(0) \\ x(2P) & x(2P-1) & \cdots & x(1) \\ \vdots & \vdots & \vdots & \vdots \\ x(L-2) & x(L-3) & \cdots & x(L-2P-1) \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_{2P} \end{bmatrix} \qquad (4)$$

Prony's suggestion was to use (4) with $L = 4P$, for which the equation is exactly determined. Having obtained the estimate $\hat{c}(z)$, the frequencies $\{F_m\}$ are computed by finding the roots of the polynomial. By (3), the roots should all be on the unit circle at conjugate pairs, the frequencies are simply the phase angles of the roots. The amplitudes and the phase angles are computed as in the maximum likelihood method.

This approach gives good results in the case of noiseless signals: the average relative error of estimation of frequency is ~ 1 %, the estimated minimal (normalized) frequency is 2×10^{-4}. It should be noted that to correctly estimate the parameters of a sinusoidal component, the method requires to cover at least 5 % of its time period.

When noise is present, the accuracy of this method deteriorates rapidly; the roots of $\hat{c}(z)$ are no longer guaranteed to be on the unit circle, however, unless the noise is very high, there will be still P pairs of complex conjugate roots.

Given the noisy nature of the sleep EEG signal, we had to modify the method to use it on real signals. The idea is to give more data to the algorithm to decrease the influence of noise and to validate the estimations thanks to the a priori information about sleep signals.

The method, commonly referred to as the *Tufts-Kumaresan method*, exploits the above idea in a sophisticated manner, and it is generally considered to be the best among the methods based on the Prony (or linear prediction) approach. Taking $L > 4P$ and increasing the order of the polynomial $c(z)$ causes the set of equation (4) to be overdetermined. From the singular value decomposition (SVD), (4) can be solved giving an estimation of the polynomial $\hat{c}(z)$, now of degree $D > 2P$, of the least possible norm [4]. The question is then how to extract the $2P$ "true" roots (the ones corresponding to the frequencies of the sinusoids) from the D roots of $\hat{c}(z)$. Tufts and Kumaresan argued that, if the noise is not too high, it is very likely that the true roots will close to the unit circle, while the noise roots will be closer to the origin [4].

In our work, the number of sinusoidal components, considered in the algorithm for each segment, has been chosen to three since, physiologically, it is very improbable to generate more than three sleep rhythmic activities in the brain at the same time. Therefore, the algorithm computes the roots of $\hat{c}(z)$ and selects the subset of $2P$ (where $P = 3$) roots whose magnitudes are closest to 1. The phase angles of these roots are the estimated frequencies. The parameters of amplitude and phase of the sinusoidal constituents can be estimated by minimizing the mean square error between the EEG signal and the reconstructed signal.
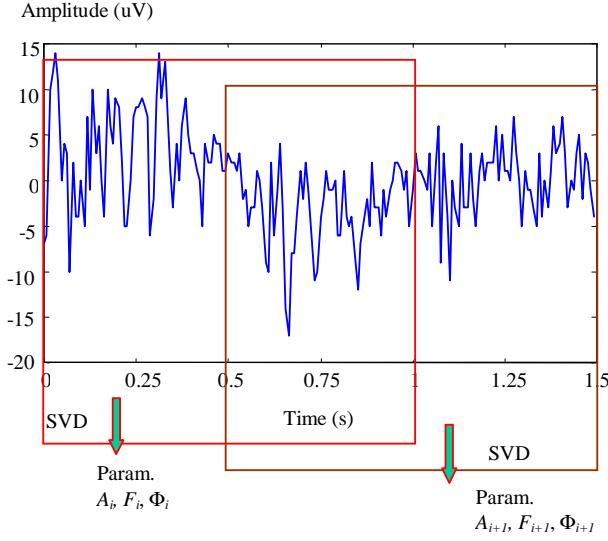
Fig. 2. - Automatic routine for the analysis of the EEG signals according to SVD method for the estimation of the parameters (frequency F_i, amplitude A_i and phase Φ_i) of the sinusoidal constituents.

It should be noted that particular care is given to the estimation of the frequency of each component. Tufts-Kumaresan method produces wildly varying estimates of the parameters when the segments being modeled contain non-sinusoidal components, like noise. In contrast, much more consistent results are obtained for segments with stable sinusoidal components, even if their amplitude is small, as in the case of spindles.

This leads to carry out controls to the estimated frequency: its value has to be included between 0 Hz and 20 Hz (the normal range of frequency for EEG sleep), it has to be coherent with the current sleep stage characteristics that involves to relate the component frequencies between each others and with the precedent estimations.

At the end of the modal analysis, the estimated parameters of the dominant sinusoidal constituents can be written as functions of time (frequency $F(t)$ and amplitude $A(t)$). They are then used to define a weighting function $\varphi(t,f)$ in two dimensions (time and frequency) as:

$$\varphi(t,f)=\begin{cases} A_i(t) & \text{if} \quad f=F_i(t) \\ 0 & \text{if} \quad f\neq F_i(t) \end{cases} \quad \text{for each} \quad i=1,2,3 \qquad (5)$$

Fig. 3 shows a simplified schematic diagram of the implemented algorithm. The effect of this function is to heighten, in the TFR, the dominant constituents proportionally to their amplitudes (refer to Fig. 4), as shown in (6)

$$\hat{S}(t,f)=S(t,f)\cdot\varphi(t,f) \qquad (6)$$

where $S(t,f)$ indicates the TFR of the EEG signal and $\hat{S}(t,f)$ is the TFR modified by the weighting function.
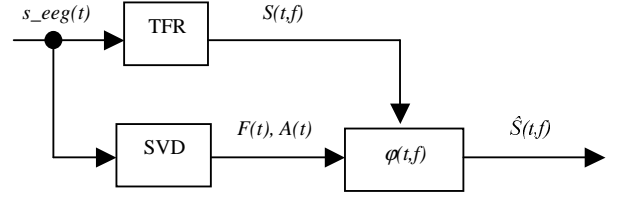

Fig. 3. Schema of the algorithm of frequency enhancement in the TFR (indicated as $S(t,f)$) of an EEG signal ($s\_eeg(t)$) by the results of SVD analysis. The filtered TFR is indicated as $\hat{S}(t,f)$.

Taking into account the values of the amplitudes of the stable constituents in the definition of the coefficients of the weighting function allows us to separate estimations of frequency resulting from the noise and significant ones generated by the brain.

The operation of filtering, applied in time - frequency transform obtained by the classic algorithms (Short Time Fourier Transform, Continuous Wavelet Transform, etc...), allows to improve not only the visual representation of the transform, but also the possibility of using a threshold to discover the transient phenomena by stressing the frequency contents locally estimated at every iteration of the process.

III. RESULTS

Fig. 4 shows (b) the results of the modal analysis compared to Short Time Fourier transform ones and (c) the result of filtering the time - frequency representation by the function defined from the modal analysis. The used signal, represented there (a), is a segment of 10 seconds of a real EEG signal during a phase of disturbed REM sleep.
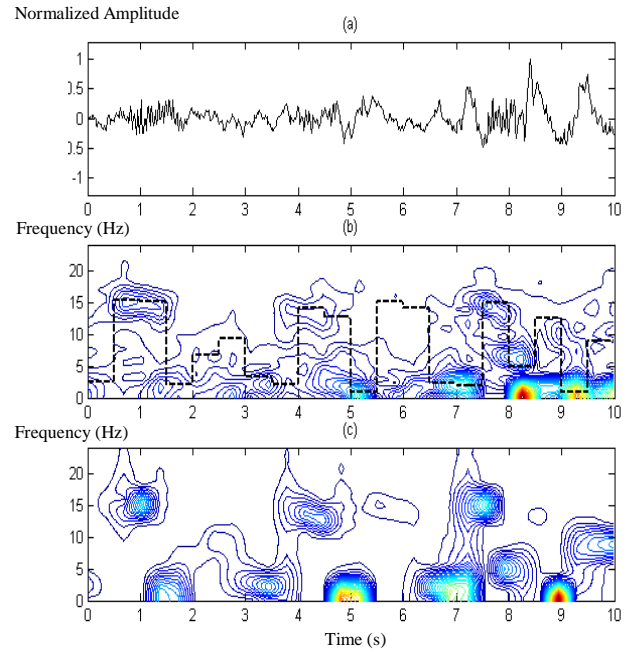

Fig. 4: (a) 10 seconds of EEG of sleep; (b) $S(t,f)$ (outlines) and modal analysis in interrupted lines (features); (c) $\hat{S}(t,f)$, the TFR of (a) modified by the result of the modal analysis.

The figure (b) shows in interrupted lines (features) the evolution of the frequency of the dominant sinusoidal constituent obtained by the algorithm in function of time.

It should be noted that this frequency is not always visible on the TFR, for example around the 6-th second. The figure (c) allows to appreciate the effect of the filtering of the representation which puts in evidence the significant constituents with high frequency (spindles), sometimes masked in the Time - frequency representation (b).

IV. DISCUSSION

It has been shown how to heighten in a TFR, certain signals of weak amplitude and high frequency, as spindles, by making sure of the stability of the frequency. So, one improves the detection of these transients in case where the visual detection is difficult or impossible. This fine study of the EEG signal is necessary to define the signature of transient events such as sleep apneas and to propose a measure of their impact on the nervous system.

A practical problem is that the Tufts-Kumaresan method involves user-chosen parameters, the number of observations L and the order D. It has been claimed, based on empirical evidence, that $D = 3L/4$ is optimal or nearly so. This is a reasonable choice only if L is relatively small, say on the order of 40 or less, to allow a fast analysis on sleep EEG data. Also, the optimal L is necessarily dependent on the number of sinusoids, their frequencies, and the signal to noise ratio, so an excessive reliance on this thumb rule is not recommended.

V. CONCLUSION

We brought an additional tool to the classic Time – frequency analysis which looks for the meaning of the most stable frequencies, that is the least scattered during the interval of observation. One so has a tool adapted to the revealing of synchronization processes in brain activity.

Moreover, the modal analysis has shown to be a particular powerful data analysis technique, if data is not purely noise driven but contains some deterministic sinusoidal components.

This technique gives a useful decomposition into artifacts (noise) and several components that represent typical EEG sleep bands (e.g. α, θ, δ activity).

The decompositions (segments, sinusoidal components) obtained can then serve as a basis for neuro-physiological model building, which might involve further steps.

An important springing of this method is to reduce the information contained in the signal in some parameters or indicators that could be correlated more easily among them, to establish possible relations between the pathologies and sleep signal. Indeed, the method allows to establish relations between the parameters of every signal and to facilitate the analysis of the correlations between the various ways of acquisition of the sleep signals.

Another advantage of the local detection of the sinusoidal parameters of the signal is the possibility to use the obtained results for the synthesis of the signals, in particular for modeling and data compression.

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